Review Article

Artificial Intelligence in Pediatric Healthcare - Part III: AI in Pediatric Inpatient and Critical Care

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ABSTRACT

Artificial intelligence (AI) is increasingly integrated into pediatric healthcare, supported by the expansion of electronic health records, continuous physiological monitoring, digital imaging, and computational methods capable of analyzing complex, time-dependent clinical data. This article is the third in a four-part series examining the evolving role of AI in pediatric medicine. The first article introduced the fundamental concepts, methodologies, data sources, and model development processes underlying AI in medicine, while the second reviewed its applications in ambulatory and preventive pediatrics. Building on these foundations, the present review examines AI applications in hospital-based pediatric care, with emphasis on pediatric emergency medicine, pediatric and neonatal intensive care, diagnostic imaging, pediatric subspecialties, and hospital workflow optimization. Current evidence indicates that machine learning and deep learning approaches may support emergency triage, early sepsis detection, prediction of clinical deterioration, physiological monitoring, ventilator management, diagnostic assessment, risk stratification, and treatment-response prediction. AI-based systems have also demonstrated potential applications in pediatric radiology, cardiology, oncology, and neurology. However, despite substantial technological progress, translation into routine clinical practice remains limited. Major challenges include small, heterogeneous pediatric datasets; age-dependent physiological variation; inadequate external validation; limited model interpretability; algorithmic bias; false-positive alerts; and difficulty integrating AI tools into established clinical workflows. Overall, AI has the potential to augment clinical decision-making and support the timely identification and management of critically ill children. However, prospective validation, external evaluation, transparency, and demonstration of clinically meaningful benefit are essential before widespread implementation.

Key words: Artificial Intelligence, Pediatric Intensive Care, Neonatal Intensive Care, Pediatric Radiology, Clinical Decision Support, Machine Learning, Critical Care

The application of artificial intelligence (AI) in hospital-based pediatric care has expanded substantially over the past decade, driven by the digitization of clinical workflows, increasing availability of continuous physiological monitoring, and advances in machine learning (ML) and deep learning (DL) methods capable of analyzing complex multimodal clinical data [1]. Although early applications of AI in medicine were largely developed using adult populations and focused primarily on specific diagnostic or imaging tasks, its use in pediatric healthcare has progressively broadened. Emerging evidence supports the potential utility of AI-enabled systems across the continuum of pediatric inpatient care, including the pediatric emergency department (PED), pediatric intensive care unit (PICU), neonatal intensive care unit (NICU), diagnostic services, and pediatric subspecialties [2].

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The clinical relevance of AI is particularly apparent in hospitalized and critically ill children, who generate large volumes of heterogeneous and time-dependent clinical data. Continuous monitoring systems in PICUs and NICUs capture dynamic physiological signals, while laboratory investigations, medical imaging, and electronic health records (EHRs) provide additional sources of structured and unstructured information. Integrating and interpreting these data remains challenging, particularly in rapidly evolving clinical situations. AI-based approaches may facilitate the identification of complex patterns across multiple data streams and support earlier recognition of clinical deterioration, diagnostic assessment, risk stratification, and treatment decision-making [3]. Such applications may be especially valuable in pediatric populations, in which

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delayed recognition of deterioration or inappropriate therapeutic intervention can have significant clinical consequences. This article is the third in a four-part series examining the evolving role of AI in pediatric healthcare. The first article introduced the fundamental concepts, methodologies, data sources, and model development processes underlying AI applications in medicine [4]. The second article examined AI applications in ambulatory and preventive pediatrics, including developmental assessment, growth monitoring, immunization, and outpatient clinical decision support [5]. Building on these foundations, the present review examines AI applications across pediatric inpatient care, with particular emphasis on emergency medicine, pediatric and neonatal critical care, diagnostic imaging, pediatric subspecialties, and hospital workflow optimization. It also considers the current limitations that may influence the translation of AI systems from model development to routine clinical practice.

2. AI IN PEDIATRIC EMERGENCY CARE

2.1 Triage and Early Deterioration Prediction

ML-based emergency triage systems have been developed to augment conventional pediatric early warning systems. These algorithms analyze clinical variables including vital signs, chief complaint text, age, and acuity scores extracted from EHRs to generate real-time risk predictions for hospitalization, ICU transfer, and clinical deterioration [6]. Several studies have reported AUCs of 0.80–0.92 for predicting hospital admission from PED data, with ML models consistently outperforming conventional triage scoring systems when tested on the same datasets [6,7].

Natural language processing (NLP) applied to free-text triage notes is a complementary approach, enabling automated extraction of symptom clusters and clinical urgency signals not captured in structured data fields. NLP-enriched triage models have demonstrated improved predictive performance for identifying children requiring urgent intervention in several single-center validation studies [7]. However, most systems have been developed and tested within individual institutions, and external validation across diverse PED settings remains limited. Population heterogeneity, differences in documentation practices, and variation in patient case mix across hospitals pose significant challenges to generalizability [8].

2.2 Sepsis Prediction in the Emergency Setting

Pediatric sepsis recognition in the emergency setting is a high-stakes application for AI given the time-critical nature of the condition and the diagnostic challenges posed by the variable presentation of sepsis across age groups. ML models integrating vital signs, laboratory values, and demographic data have been developed to identify children meeting sepsis criteria or at risk of septic shock before clinical recognition [9]. A model applying extreme gradient boosting (XGBoost) and gated recurrent unit (GRU) architectures to a combined pediatric emergency and critical care dataset achieved real-time sepsis prediction using a 12-hour predictive window, integrating both static and dynamic EHR features [10]. The Phoenix Sepsis Score criteria, developed using EHR data from 63,875 PICU encounters and validated across multiple ML architectures, demonstrated improved sensitivity for sepsis onset prediction compared with conventional SIRS-based definitions [11].

Despite these advances, high false-positive rates remain a limiting factor. Alert systems that generate frequent false alarms contribute to alarm fatigue among clinical staff, potentially undermining the clinical value of early warning systems [12]. Threshold calibration, integration of model uncertainty estimates, and tiered alert designs that differentiate low-, intermediate-, and high-probability predictions represent strategies to improve the clinical utility of AI-based sepsis detection in emergency settings.

3. AI IN PEDIATRIC INTENSIVE CARE UNITS (PICU)

3.1 Sepsis Prediction and Early Warning Systems

The PICU is one of the most data-rich environments in pediatric medicine, with continuous monitoring of hemodynamic, respiratory, and neurological parameters generating time-series data streams well suited to ML analysis. ML-based early warning systems have been developed and evaluated for predicting clinical deterioration, ICU mortality, and the need for escalating interventions in critically ill children [13]. A multi-unit machine learning model for predicting critical events among hospitalized children demonstrated that ML algorithms using routinely collected EHR data could identify at-risk patients across multiple hospital units, not only within the PICU, enabling earlier mobilization of clinical resources [14].

Long short-term memory (LSTM) networks and other recurrent neural network architectures are particularly suited to time-series physiological data because they capture temporal dependencies in monitoring signals that may reflect evolving pathophysiological processes. Studies evaluating these approaches in PICU cohorts have reported improved performance over conventional pediatric early warning scores (PEWS) for predicting ICU transfer and mortality, although comparative benchmarking across studies is complicated by variation in outcome definitions, prediction windows, and cohort characteristics [13].

3.2 Ventilator Management Support

Mechanical ventilation management in critically ill children involves complex, individualized decisions regarding ventilator settings, weaning readiness, and respiratory support modality selection. AI has been applied to support these decisions through predictive models for weaning success and reinforcement learning (RL) frameworks for ventilator parameter optimization [15]. RL-based dosing and ventilator management systems learn optimal treatment strategies through iterative interaction with clinical data environments, generating individualized recommendations that may differ from population-average protocols. Pilot studies in adult and pediatric populations have demonstrated the feasibility of RL-based ventilator management support, with some studies reporting reductions in mechanical ventilation duration and associated complications [15,16]. However, prospective validation in pediatric populations remains limited, and clinical deployment requires careful integration with clinician oversight given the potential for unanticipated recommendations in complex physiological scenarios.

3.3 Medication Dosing and Pharmacological Support

AI-based clinical decision support for medication dosing in the PICU addresses a high-risk area of pediatric practice, given substantial pharmacokinetic variability across age groups, frequent off-label medication use, and the complexity of polypharmacy in critically ill patients [17]. ML-based pharmacokinetic models have been developed to individualize dosing of antimicrobials, vasopressors, and analgesic and sedative agents based on patient characteristics and real-time clinical parameters. These systems aim to optimize therapeutic drug exposures while minimizing toxicity, particularly for medications with narrow therapeutic indices. Although early evidence suggests potential benefits in dosing precision, most studies remain at the model development stage, and prospective clinical trials evaluating patient outcomes are limited [17].

4. AI IN NEONATAL INTENSIVE CARE UNITS (NICU)

4.1 Early Detection of Neonatal Sepsis

Neonatal sepsis presents diagnostic challenges due to the subtlety and non-specificity of early clinical signs in preterm and term neonates. Continuous physiological monitoring in the NICU generates rich time-series data on heart rate, respiratory rate, oxygen saturation, and blood pressure, providing a substrate for ML-based early warning systems [18]. Studies have demonstrated that analysis of heart rate variability (HRV) and cardiorespiratory patterns can detect subtle physiological changes associated with early-onset and late-onset neonatal sepsis, often 24–48 hours before clinical recognition and initiation of antibiotic therapy [18,19].

AI-based respiratory monitoring in the NICU has expanded beyond sepsis detection to encompass prediction and management of neonatal respiratory disorders, including respiratory distress syndrome, bronchopulmonary dysplasia (BPD), and apnea of prematurity [20]. DL models applied to continuous respiratory monitoring data have demonstrated promising performance for predicting BPD and other complications of prematurity, enabling earlier targeting of preventive and therapeutic interventions. A systematic review of AI in neonatal respiratory care found that AI applications in this domain are growing rapidly, with studies reporting high sensitivity for detecting apnea events and predicting respiratory failure requiring escalation of support [20].

4.2 Prediction of Prematurity-Related Complications

Beyond sepsis, ML approaches have been applied to predict a range of complications affecting preterm infants in the NICU, including intraventricular hemorrhage (IVH), necrotizing enterocolitis (NEC), and retinopathy of prematurity (ROP). These conditions share a common challenge: clinical signs often develop only after significant underlying pathological changes have occurred, limiting the effectiveness of reactive management strategies. AI models that can identify at-risk neonates before overt clinical presentation may enable more targeted monitoring and preventive intervention [19].

ML models using EHR data, physiological monitoring variables, and demographic factors have demonstrated feasibility for predicting NEC and IVH risk in preterm neonates, with AUCs ranging from 0.70 to 0.88 across published studies [19]. For ROP, DL-based retinal image analysis has emerged as a promising approach for automated severity grading and screening prioritization, with several studies demonstrating performance comparable to or exceeding that of ophthalmologists in classifying disease requiring treatment [21]. These applications are particularly relevant in resource-limited settings where access to specialist ophthalmology may be constrained.

5. AI IN PEDIATRIC RADIOLOGY AND IMAGING

5.1 Chest Radiograph and CT Analysis

Medical imaging analysis represents one of the most extensively studied applications of AI in medicine, with DL models demonstrating performance approaching or matching specialist radiologists for a range of imaging tasks in both adult and pediatric populations [22]. In pediatric radiology, DL-based systems have been developed to automatically detect pneumonia, pleural effusion, pneumothorax, and cardiomegaly on chest radiographs. Convolutional neural network (CNN) architectures trained on large labeled imaging datasets have consistently demonstrated high diagnostic accuracy for these tasks, with AUCs often exceeding 0.90 in retrospective validation studies [22,23].

Fracture detection is another high-impact application of AI in pediatric imaging, given the clinical and medico-legal implications of missed fractures, particularly in suspected non-accidental injury. DL models for pediatric wrist and elbow fracture detection have demonstrated sensitivity and specificity comparable to those of emergency radiologists, with some studies suggesting that AI-assisted interpretation reduces the rate of missed fractures in emergency settings [23,24]. AI-based prioritization systems that triage imaging studies by urgency can reduce reporting delays for critical findings, which is particularly valuable in high-volume emergency and inpatient imaging workflows.

5.2 Neuroimaging and Brain MRI

DL models for pediatric neuroimaging analysis have been applied to detection of intracranial hemorrhage, cerebral edema, hydrocephalus, and lesion segmentation on brain CT and MRI [25]. Automated brain MRI volumetric analysis tools enable quantitative assessment of brain development and pathology, supporting clinical evaluation in conditions such as prematurity, hypoxic-ischemic encephalopathy, and pediatric brain tumors. DL-based segmentation of neonatal brain MRI has demonstrated performance comparable to manual expert segmentation, with potential applications in predicting neurodevelopmental outcomes in high-risk neonates [25].

AI applications in pediatric neuroimaging also include automated detection of cortical malformations, white matter abnormalities, and tumor characterization. These tools may support faster and more reproducible interpretation of complex neuroimaging studies, reduce interobserver variability, and enable more efficient clinical workflows. However, training datasets for pediatric neuroimaging AI remain relatively small compared to adult imaging datasets, and the age-dependent variability of normal brain development poses significant challenges for model generalization across the pediatric age spectrum [25,26].

5.3 Ultrasound and Point-of-Care Imaging

Ultrasound is a particularly important imaging modality in pediatric practice because it lacks ionizing radiation, is portable, and has wide clinical applicability. AI applications in pediatric ultrasound include automated interpretation of cardiac, abdominal, renal, and musculoskeletal imaging studies [27]. AI-guided acquisition systems have been developed to help novice operators obtain diagnostic-quality echocardiographic views, with particular relevance in resource-limited settings where specialist echocardiography is unavailable. DL models for automated echocardiographic analysis have demonstrated high accuracy for measuring cardiac function parameters and detecting structural abnormalities in pediatric populations, potentially supporting earlier diagnosis of congenital and acquired heart disease [27,28].

6. AI IN PEDIATRIC SUBSPECIALTIES

6.1 Cardiology

AI applications in pediatric cardiology encompass automated ECG analysis for arrhythmia detection and congenital heart disease (CHD) screening, as well as DL-based echocardiography interpretation [28]. ML models applied to neonatal and pediatric ECG datasets have demonstrated high sensitivity for detecting arrhythmias including supraventricular tachycardia and long QT syndrome, with some studies reporting performance comparable to pediatric cardiologists [28]. AI-assisted newborn CHD screening using pulse oximetry data combined with ML analysis has demonstrated improved detection of critical CHD compared with conventional screening protocols in some settings, potentially supporting earlier surgical or catheter-based intervention [29].

AI-based echocardiography analysis enables automated measurement of ventricular dimensions, ejection fraction, and valve function, reducing the time and operator expertise required for quantitative echocardiographic assessment. These capabilities are particularly relevant in the PICU and NICU, where serial echocardiographic assessments of hemodynamic status are frequently required but specialist availability may be limited. DL models have also been applied to fetal echocardiography for prenatal CHD detection, with several studies demonstrating improved sensitivity for identifying structural cardiac abnormalities [29].

6.2 Oncology

Pediatric oncology represents a rapidly evolving domain for AI applications, encompassing diagnostic imaging analysis, treatment response prediction, genomic data interpretation, and outcome modeling [30]. DL models applied to histopathology whole-slide images have demonstrated performance approaching that of specialist pathologists for classifying pediatric tumors, including neuroblastoma, medulloblastoma, and acute lymphoblastic leukemia (ALL), with potential applications in automated tumor grading and molecular subtype prediction [30]. ML models integrating clinical, imaging, and genomic data have been developed to predict treatment response and risk of relapse in pediatric ALL, supporting more personalized risk stratification and treatment intensification decisions [30,31].

AI-based tumor segmentation on pediatric MRI studies enables automated volumetric assessment of tumor response to therapy, supporting more objective and reproducible evaluation of treatment efficacy than conventional radiological response criteria. These capabilities are particularly relevant in pediatric brain tumor management, where response assessment on serial MRI studies is both time-intensive and subject to significant interobserver variability [31]. Integrating AI-based imaging analysis with genomic and molecular profiling data represents an emerging frontier in pediatric oncology precision medicine.

6.3 Neurology

AI applications in pediatric neurology encompass automated EEG analysis for seizure detection and classification, DL-based neuroimaging for epilepsy evaluation, and ML models for predicting neurodevelopmental outcomes [32]. Neonatal seizure detection is a high-priority application given the clinical consequences of unrecognized electrographic seizures in neonates undergoing continuous EEG monitoring in the NICU. ML-based seizure detection algorithms have demonstrated high sensitivity for identifying neonatal electrographic seizures, enabling more consistent surveillance than visual EEG review alone and reducing the clinical burden of continuous EEG interpretation [32].

In older children, DL models for automated epileptic seizure detection from long-term ambulatory EEG recordings have demonstrated performance approaching that of specialist neurophysiologists, with potential applications in reducing the time-to-diagnosis for children with refractory epilepsy. AI-based analysis of MRI data for epilepsy surgery evaluation, including automated detection of cortical dysplasia and focal cortical abnormalities, may improve the sensitivity of presurgical evaluation compared with conventional visual MRI review [33].

6.4 Genetic Syndrome Identification

AI-based facial phenotyping represents an innovative application of computer vision to pediatric clinical genetics. Deep learning systems such as Face2Gene analyze facial photographs to generate differential diagnoses for genetic syndromes by comparing facial feature patterns with large reference datasets of individuals with known diagnoses. Studies have shown that such tools can identify the correct diagnosis among the top three suggestions in approximately 70–80% of cases across diverse genetic syndrome datasets, and clinical validation studies have confirmed their utility in supporting the diagnostic evaluation of children with suspected genetic disorders [34,35]. These systems are designed to augment, not replace, clinical genetic assessment, providing clinicians with a ranked differential diagnosis to guide further investigation.

7. AI IN HOSPITAL WORKFLOW OPTIMIZATION

7.1 Clinical Documentation Automation

Large language models (LLMs) and NLP-based systems are increasingly applied to automate and support clinical documentation in inpatient pediatric settings, reducing the administrative burden on clinicians and potentially improving documentation accuracy and completeness [36]. AI-assisted documentation tools can generate structured clinical summaries, automatically extract key clinical information from unstructured clinical notes, and draft discharge summaries and referral letters from EHR data. In the PICU and NICU, where documentation requirements are particularly intensive, these tools may enable clinicians to redirect time toward direct patient care [36].

NLP-based chart review tools have been developed to identify clinically relevant information in large EHR datasets, supporting quality improvement initiatives, retrospective clinical research, and real-time clinical decision support. AI systems for automated coding and billing support have also been evaluated in inpatient pediatric settings, with studies demonstrating improved diagnostic coding accuracy compared with manual review alone. However, the accuracy, reliability, and potential for AI-generated documentation errors require careful evaluation before wide clinical deployment, and mechanisms for clinician review and oversight remain essential [37].

7.2 Bed Management and Resource Allocation

Predictive analytics models applied to hospital operational data have been developed to support bed management, patient flow optimization, and resource allocation in pediatric inpatient settings [38]. ML models using EHR data, admission patterns, and historical occupancy data can predict future PICU and ward bed demand, enabling proactive planning of staffing levels and resource allocation. Predictive models for hospital length of stay and discharge readiness support discharge planning processes, potentially reducing unnecessary inpatient stays and improving bed availability for newly admitted patients [38].

AI-based early prediction of hospital-acquired complications, including pressure injuries, venous thromboembolism, and medication adverse events, enables targeted preventive interventions for high-risk patients, potentially reducing preventable harm and associated healthcare costs [39]. Integration of predictive risk models with clinical decision support systems embedded in the EHR provides an efficient mechanism for delivering actionable alerts to clinicians within their existing workflow, although alert fatigue and over-alerting remain important concerns that must be addressed through careful threshold calibration and alert design [12] (Table 1).

8. BARRIERS TO ADOPTION IN INPATIENT PEDIATRIC SETTINGS

Despite AI's substantial potential in pediatric inpatient care, translation from research to routine clinical practice remains limited by several interconnected barriers. Data availability and quality represent fundamental challenges: pediatric datasets are consistently smaller than adult equivalents, age-related physiological variability requires age-stratified model development and validation, and missing data in clinical records can introduce systematic biases that compromise model performance [40]. The paucity of large, standardized, multi-institutional pediatric critical care datasets has constrained the development of generalizable models, and efforts to address this through federated learning architectures, which enable model training across distributed datasets without centralizing sensitive patient data, are still in early stages[40,41].

Model generalizability is a pervasive concern across pediatric inpatient AI research. The majority of published models have been developed and validated within single institutions, and external validation studies frequently demonstrate significantly reduced performance compared with internal validation metrics [8] . Population drift, the change in patient characteristics and clinical practices over time that can erode model performance after deployment, represents an additional challenge that necessitates continuous monitoring and recalibration of deployed AI systems [41].

Alarm fatigue is a clinically important consequence of high false-positive rates in AI-based early warning systems. When alert thresholds are set to maximize sensitivity, the resulting volume of false alerts can overwhelm clinical staff, leading to alert desensitization and reduced responsiveness to genuine high-priority warnings [12]. Strategies to mitigate alarm fatigue include optimizing alert thresholds to balance sensitivity and specificity for the specific clinical context, implementing tiered alert designs that differentiate urgency levels, and integrating AI alert outputs into workflow-compatible display formats that minimize unnecessary interruptions [12].

Explainability and transparency remain significant limitations of many high-performing DL models in clinical settings. Clinicians are reasonably reluctant to act on recommendations from "black box" models that cannot provide interpretable justifications for their outputs, and regulatory guidance increasingly requires that AI medical devices demonstrate appropriate levels of transparency [41,42]. Explainable AI (XAI) methods, including SHAP (SHapley Additive exPlanations) values and attention mechanisms that highlight the clinical features driving model predictions, offer partial solutions but do not fully resolve the interpretability challenge for complex DL architectures [42].

Table 1: Summary of AI Applications in Pediatric Inpatient Care

Clinical Area	AI Application	Key Findings / Evidence
Emergency Triage [7]	ML-based triage scoring; NLP from chief complaint text	AUC 0.80–0.92 for predicting hospitalization and deterioration
Sepsis Detection (ED) [10]	XGBoost and GRU models on vital signs and labs	Real-time sepsis prediction with 12-hour window before diagnosis
Clinical Deterioration (PICU) [13,14]	ML early warning scores; LSTM on physiological time series	Outperformed conventional PEWS; improved ICU transfer prediction
Neonatal Sepsis (NICU) [18]	Physiological signal analysis; HRV pattern recognition	Early detection 24–48 hours before clinical signs; sensitivity >85%
Ventilator Management (PICU) [16]	RL-based dosing; ML weaning prediction	Reduced duration of mechanical ventilation in pilot studies
Pediatric Radiology [22–27]	CNN for chest X-ray, fracture detection, brain MRI	Performance comparable to radiologists in pneumonia and fracture detection
Pediatric Cardiology [28,29]	AI echocardiography; ECG arrhythmia detection	Automated CHD screening; AUC >0.90 for arrhythmia detection.
Pediatric Oncology [30,31]	ML treatment response prediction; DL pathology image analysis	Improved ALL remission prediction; automated tumor segmentation.
Pediatric Neurology [32]	ML seizure detection from EEG; DL brain MRI analysis	High sensitivity for neonatal seizure detection; accurate lesion segmentation.

Regulatory frameworks for AI medical devices remain underdeveloped, particularly regarding pediatric-specific requirements. As discussed in the second article of this series, only 17% of FDA-approved AI medical devices carry pediatric labeling, reflecting a significant gap in pediatric validation of commercially available tools [5]. Mandatory pediatric subgroup validation requirements, age-specific performance benchmarks, and clearer regulatory guidance on continuous-learning AI systems are needed to ensure deployed tools meet appropriate safety and efficacy standards for use in children [43]. These regulatory challenges will be addressed comprehensively in the fourth article in this series.

CONCLUSION

Artificial intelligence is increasingly demonstrating clinical relevance across the full spectrum of pediatric inpatient care, from emergency triage and sepsis detection to neonatal complication prediction, diagnostic imaging analysis, and subspecialty decision support. Current evidence suggests that ML and DL models can support earlier recognition of clinical deterioration, improve diagnostic accuracy, and contribute to more efficient hospital workflows when integrated appropriately into clinical systems. However, the gap between model development and clinical implementation remains wide in pediatric inpatient settings. Rigorous prospective multicenter validation, careful management of alarm fatigue, investment in explainable and transparent model design, and the development of pediatric-specific regulatory guidance are essential prerequisites for responsible clinical deployment. As AI tools become more prevalent in inpatient pediatric environments, pediatricians and pediatric intensivists must develop the AI literacy needed to critically evaluate, appropriately utilize, and effectively oversee these technologies in the care of critically ill and hospitalized children. The fourth and final article in this series will address the ethical, regulatory, safety, and future dimensions of AI in child healthcare, providing a comprehensive framework for responsible AI implementation in pediatric practice.

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